

## Modeling and Monitoring Ecosystem Performance

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## Introduction

Our method of monitoring ecosystem performance can help scientists and land managers understand changes in the productivity of ecosystems over large areas. We use the Normalized Difference Vegetation Index (NDVI) as a surrogate for ecosystem productivity. By itself, a time series of NDVI is strongly influenced by year-to-year variations in climatic conditions (temperature and moisture). Climatic variability makes it difficult to detect the variations that are caused by nonclimatic effects such as land management, insect infestations, fires, and changing soil conditions associated with permafrost degradation. We develop a model of the expected ecosystem performance on a sample of image pixels and account for site potential and yearly variations in climate. We then compare the results of the model with the actual NDVI for a growing season and highlight areas that are performing better or worse than expected. The result is a powerful technique for detecting perturbations to ecosystems. The method is applicable to many types of ecosystems and many different disturbances, particularly to water-limited systems which may experience large interannual variations. Three successful prototype studies are illustrated here.

The methods are ready to become operational, forming a basis for a national plan for ecosystem monitoring, which in turn is needed to understand how to develop policies in response to changing natural and socioeconomic conditions.

## Methods

The NDVI\* for this method can be computed from coarse or moderate resolution sensors, including the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS), or SPOT VEGETATION. NDVI has been used as a surrogate for photosynthetic activity (Goetz et al. 2005) and has been shown to be correlated with biomass (Wylie et al. 1991) and carbon fluxes (Gilmanov et al. 2005). We use the growing season NDVI (GSN) as a proxy for yearly ecosystem performance. The GSN is the integral under a curve of NDVI for a growing season. Sensors with moderate spatial resolution have a high enough temporal resolution to have a meaningful integration over time. The GSN for each year and a long-term GSN are computed for each pixel. With a substantial period of record of remotely sensed data and powerful statistical techniques, we are able to identify trends in ecosystem performance for the entire period or for targeted segments of time.

\*NDVI is the difference between the infrared and red reflectance values normalized by dividing by the sum of the infrared and red reflectances.

To build the model for expected ecosystem performance, a large number (5,000 to 10,000) of random points within a land cover type are selected, and image data are extracted for multiple years (fig. 1).

These random points are stratified to get equivalent representation of high, medium, and low values of GSN. Data on climate and site potential are also developed for the selected points. The resulting database represents the spatial and temporal variability of GSN in the study area and includes variables that explain the environmental conditions that affect ecosystem performance. If site potential estimates are not directly available (e.g., from soil maps), we estimate site potential using a long-term average GSN and other nonclimatic variables. Seasonal summaries of climatic data are aggregated from monthly datasets (PRISM†).

†Parameter-elevation Regressions on Independent Slopes

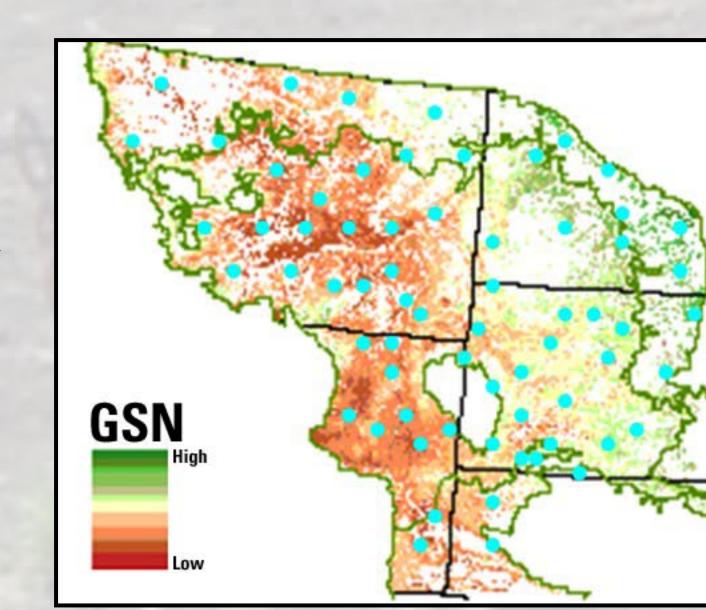


Figure 1. A schematic view of selecting random points () in the northern Great Plains grasslands.

## Methods continued

The expected ecosystem performance is operationally defined in terms of a modeled GSN. The model is fit to site potential variables (including elevation, slope, aspect, soil, and other regional datasets) and to climate variables (fig 2). By fitting the model for both productive (wet) and less productive (dry) years, the model is robust for estimating ecosystem performance for pixels that are not used in the training dataset (Wylie et al. submitted).

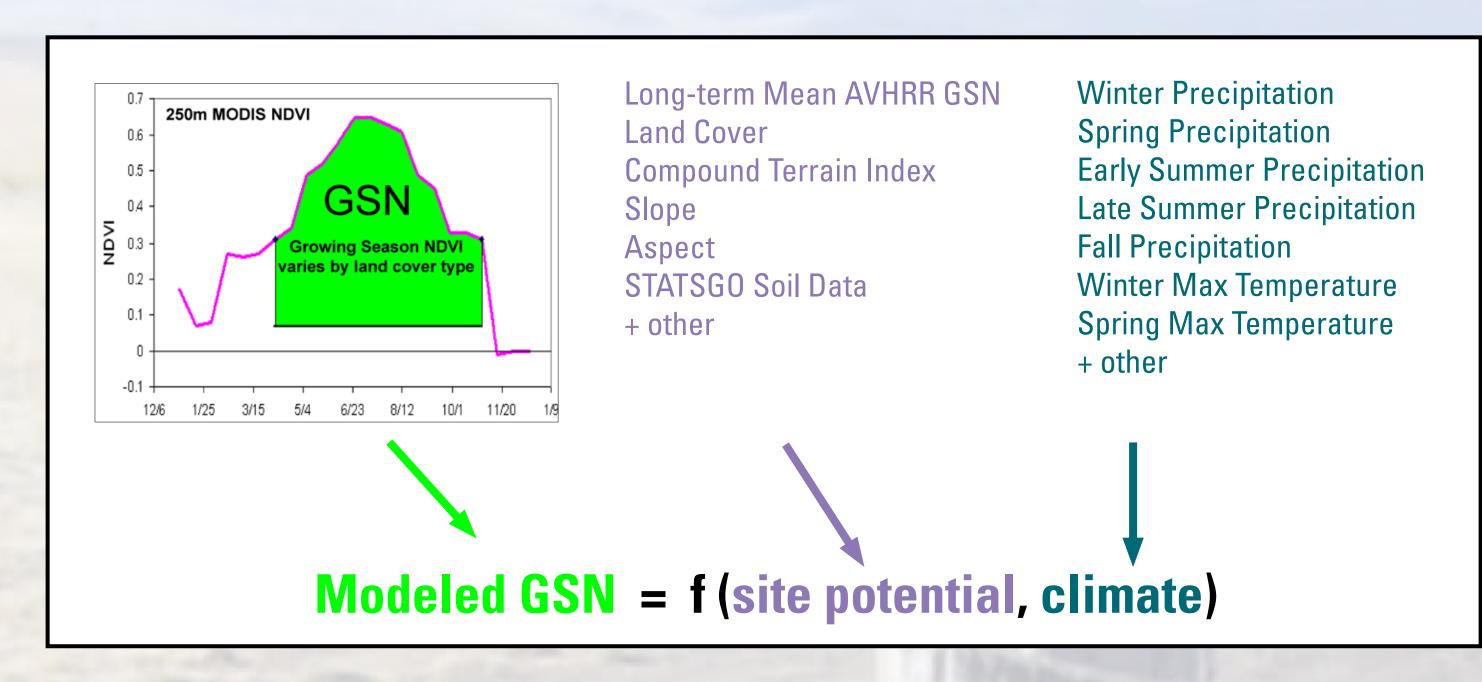


Figure 2. Model inputs for estimating multiyear and multisite GSN.

We use machine learning techniques based on regression trees to derive piecewise regression models (Cubist software). Variables used to predict GSN can serve to divide the modeling domain (e.g., Rule 1/1, pptspr less than or equal to 21) or to act as an independent variable in the regression equations for the rules (fig. 3). Long-term NDVI was used as a proxy for site potential in this model. Regression tree or piecewise regressions are relatively insensitive to outliers.

We find areas of ecosystems that are performing differently than expected by comparing (fig. 4) the actual GSN values (y-axis) to the modeled GSN values (x-axis). Anomalies below the lower 90 percent confidence interval (magenta) are performing at a lower level than expected based on climatic conditions. Anomalies above the upper 90 percent confidence interval (green) exceed the expected performance based on climatic conditions. The zone between the 90 percent confidence limits (buff) represents variation that is not statistically significant.

For each year in the study, we make maps of expected GSN and the performance anomaly. We evaluate trends by mapping the frequency of overperformance or underperformance across a set of years. By fitting a linear regression to the anomaly measures through time, we can identify statistically significant changes in ecosystem performance. These trends in the performance anomaly may be related to degradation, natural hazards, plant succession, stressed ecosystems, or management (e.g., agricultural practices).

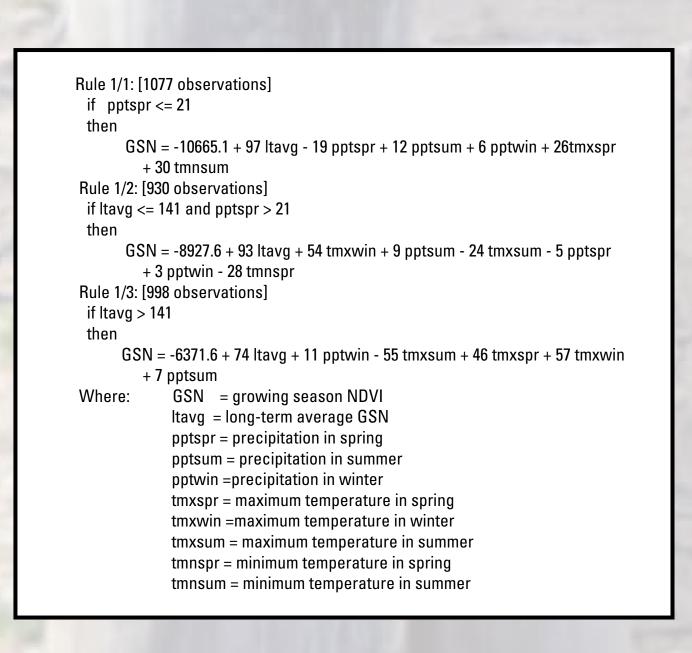
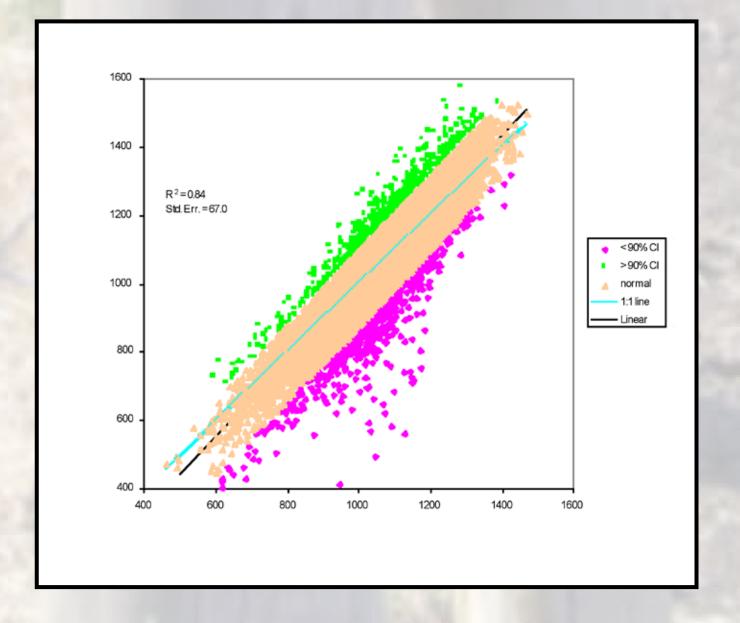


Figure 3. Example piecewise regression model.

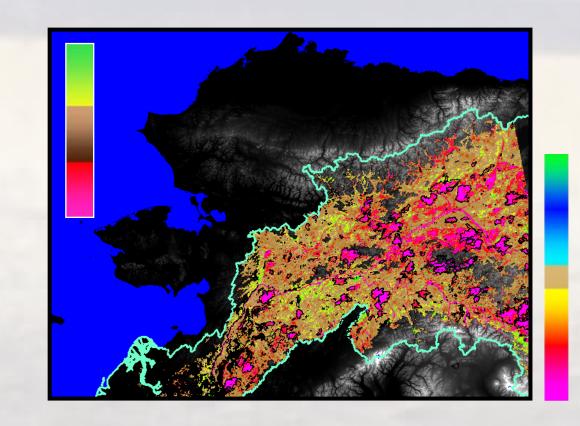


**Figure 4.** Defining anomalous ecosystem performance for the boreal forest in the Yukon River Basin (R2 = 0.84).

## Results

#### **Yukon River Basin**

Areas with underperformance in 2004 (magenta) often align with areas that burned between 1996 and 2004 (fig. 5, left panel). In some areas, a decreasing trend (1996 to 2004) was observed although there were no recent fires (fig. 5, center panel). The negative trend in anomalies may identify recent insect infestations. Future work will model the entire basin in cooperation with the Canada Centre for Remote Sensing.



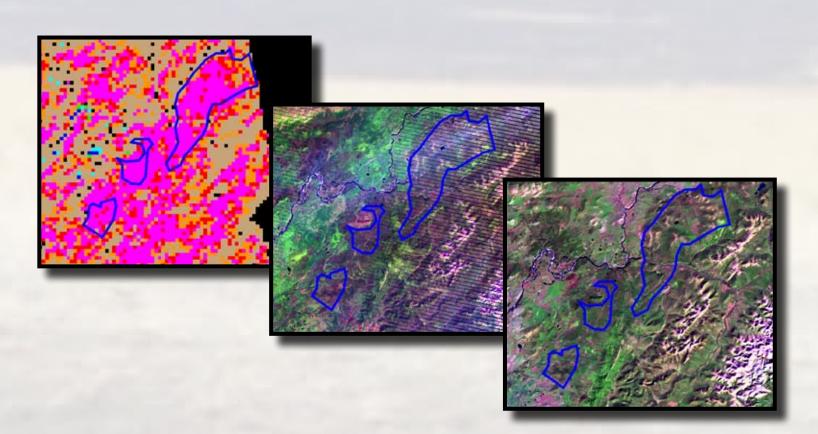


Figure 5. Performance anomalies in 2004 in the Yukon River Basin (left), trends in the anomalies for a selected area (center), and Landsat images for the selected area (right).

#### **Wyoming Sagebrush**

Areas with degraded lands (overgrazing, mining) were underperforming, and areas with tree and shrub mixtures were typically overperforming (fig. 6). Validation with Landsat-derived estimates of bare ground agreed with underperforming areas 66 percent of the time. The model captured the essential site potential and climatic variables for this ecosystem (R2 = 0.96).

# Figure 6. Multiple year frequency of performance anomalies in shrub (sagebrush) ecosystems of Wyoming.

### Idaho Sagebrush Steppe

Different models were developed for grasslands and shrub areas, with R2 of 0.95 and 0.86, respectively. Performance anomalies highlighted differences in livestock intensities (fence lines are shown in fig. 7). The relationship between stocking rate data and performance anomaly was stronger on grassland areas (R2 = 0.94) than on shrub areas (R2 = 0.44).

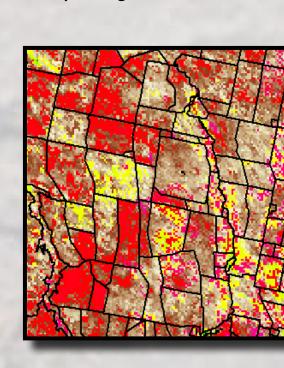


Figure 7. Performance anomaly in 2007 for Idaho shrublands.

## Conclusions

The method presented here is robust within ecosystems and can be applied in very different environments (semiarid to boreal). We control for climatic variations so that nonclimate changes are apparent. We identify stressed areas which may be susceptible to additional change. The methods would support an operational national plan for ecosystem monitoring.

## References

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## Acknowledgements

This research was funded by USGS Dynamic Ecosystem Performance (Land Remote Sensing) and Quantitative Models in Alaska (Earth Surface Dynamics) projects.

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